INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

REVIEW ARTICLE

OPEN ACCESS

Received: 04-03-2023

Accepted: 06-05-2023

Published: 04-07-2023

Citation: Varpe K, Sakhare S (2023) Review of Character Recognition Techniques for MODI Script. Indian Journal of Science and Technology 16(26): 1935-1946. https://doi.org/10.17485/IJST/v16i26.485

* **Corresponding author**.

kanchanv2007@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Review of Character Recognition Techniques for MODI Script

Kanchan Varpe[1]*, Sachin Sakhare[2]

1 Research Scholar, Department of Computer Engineering, Vishwakarma Institute of Information Technology, Pune, 411048, India
2 Professor, Head, Department of Computer Engineering, Vishwakarma Institute of Information Technology, Pune, 411048, India

Abstract

Objectives: The main objective of this study is to review and compare the various methods used for Modi script recognition. **Methods:** The author has chosen various methods from 2010 to 2022 that are used to process MODI Script. The distinct methods employed for feature extraction and classification are compared for various datasets. A discussion on the significance of the selection of correct feature extraction and classification techniques and the comments on the methods suited to specific applications is provided. **Findings:** Currently, there are very few MODI translators. In contrast, millions of historical documents written in MODI remain unexplored. **Novelty:** The Convolutional Neural Networks (CNNs) has been used successfully for recognizing MODI Script characters. In the present study the author finds that, compared to all techniques, CNN provides maximum accuracy of 99.78%. Hence, CNN is the best character recognition technique for the MODI script.

Keywords: Distance Classifier; Feature Extraction; and Classification; Handwritten Characters; MODI Lipi; Character Recognition

1 Introduction

The Marathi language is primarily written in MODI, a Brahmi-based language. Up until 1950, when everyone shifted to the Devanagari character, the MODI character was widely used. Writing formal papers, cultural writings, and sacred publications all used the MODI alphabet. In this consequence, MODI Script was most frequently used in ancient writing from the 12th century to the 19th century in Maharashtra state of India. However, the screenplay is still unknown to the majority of people. The research focuses in this paper is concentrated on the recognition of handwriting characters and their translation into the Marathi language[1].

The MODI language was in use until the 20th century and traces back to the 12th century. The MODI Script has been used by the Peshava Kalin Kingdom and Shivkalin for documentation. Figure 1 displays the message written by Ch. Shivaji Maharaj in Modi script. The MODI writing formats underwent numerous modifications over the time. The MODI Script was originally known as "Adyakalin" in the 12th century, and it changed into "Yadavkalin" in the 13th century. The "Bahamanikalin" of the 14th to 16th centuries, followed by the "Shivakalin" of the 17th century, represents the subsequent stage of growth[2].

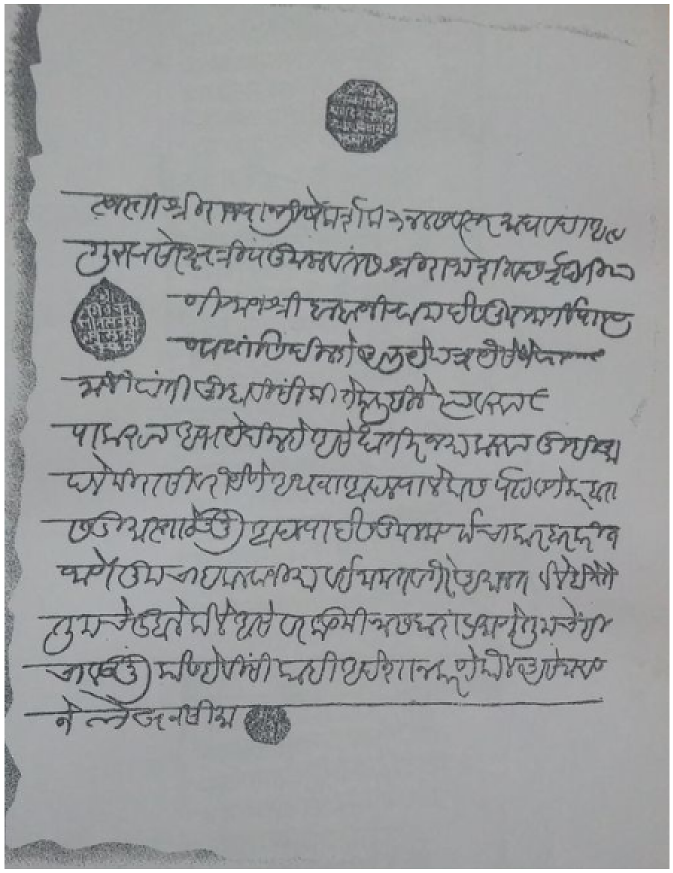

Fig 1. Illustrate the letter written by Chh. Shivaji Maharaj in MODI Script [Source: Language Services Bureau]

The Modi lipi or script originated as a cursive style of writing Marathi. This script was in use for close to 600 years, primarily from the 14th century BC up until the 1950s. From that point in time, the Modi Lipi was replaced by the Devanagari or Balbodh script for use in written Marathi. Modi Lipi is written using the cursive style of writing making it arduous to read. It was this style that made it possible for the Modi Lipi to be used for faster writing as a sort of shorthand script. Indian scripts fall into two major categories: those with the shirorekha or head bar and scripts without the head bar. Modi Lipi belongs to the former category. A significant property of the Modi Lipi is that, as a rule, it is written without lifting the pen. This is what gives the script its cursive characteristic. It does not factor in the length of the vowel and unlike Indic scripts such as Devanagari and others; it does not include conjunct consonants. In addition, the Modi script was utilized for encrypting messages as all the people were not well versed in reading the Modi Lipi[3,4].

1.1 Rationale of the Study

Since 1950 Marathi language uses the Devanagari script instead of MODI however, a majority of the historical documents that are stored in the archives are all scripted in MODI. Presently there are very few experts who are capable of transliterating documents that are written in MODI to another language or understandable form. Hence restoring these documents has become a complicated task. This is the inspiration for developing a system that is capable of recognizing text written in the documents using the MODI Lipi and preserving them for the future[5].

These historically significant documents have been scripted in MODI with major differences in the style of writing which includes crucial representation of characters in cursive form and compound character styles. Very little research effort has been put into the digitization of historical documents using character recognition in MODI Lipi. These documents were created on paper and cloth material and some with wooden cover pages. It is very complicated to maintain paper material documents for a long duration[6]. It has been more than 50 years since those precious documents were drawn up and some of them are about to degrade due to inappropriate facilities to maintain them. Many records that are stored in places like private libraries, temples, school records, and historical palaces are maintained in detrimental conditions. Hence digitization of these huge numbers of historical documents is necessary [7], [8]. The main rationale of the research is the digitization of MODI Lipi to preserve historical documents.

1.2 Significance of the Study

The digitization of Modi script is not only a requirement of India but also other countries such as Europe, South Asia, Denmark, etc. These countries also have preserved historical documents written in MODI Lipi. In India, Maharashtra state has various archives with greater parts of these documents. Ample historical 'MODI' documents are being stored in the following archrivals:

- Bharat Itihas Sanshodhan Mandal, Pune (BISM)
- Rajwade Sanshodhan Mandal, Dhule (MS, India)
- Tanjawar's Saraswati Mahal
- Oriental manuscript section of Chennai's Connemara University
- Maratha History Museums, Deccan, Pune.

Before 1950 the use of Modi Lipi was extended to various routine activities like business accounts, education, managerial documentation, and journalism. All these historical documents provide valuable information about the history of Maharashtra in the field of politics, sociology, and economics. There were various types of documents like zamindars (land records), Taleb (balance sheets), rocking (military papers), decades (village records), nivadpatras (judicial paper), kaifiyats (questionnaires or narratives), and documentation regarding matters of property [9,10].

In previous papers, researchers used different techniques to identify the implementation of the extraction of wavelet transform-based features for character recognition of the Modi Lipi, and they used different methods based on a convolutional autoencoder for recognizing handwritten MODI script. But due to few reasons, the outcome was not 100% accurate. In this paper, the author reviews various papers about the Modi script to find out the best method for the identification of Modi lipi. This paper addresses techniques being used in identified contributions of Modi Lipi Recognitions.

1.3 Literature Survey

Joseph S., et al. (2022) [11] in this work authors discuss the implementation of the extraction of wavelet transform-based features for character recognition of the Modi Lipi. For the experimentation, the authors have used Daubechies, Haar, and Symlet wavelets, and have compared the various mother wavelets they used as a decision tree classifier for the procedure of classification. To undertake this experimentation, a total of 4600 characters of the MODI script were used out of which 3220 were set aside for training samples and 1380 were set aside for testing samples. The outcome has shown that Daubechies wavelet was 91.75% accurate in recognizing the MODI characters.

Joseph S., et al. (2021) [12] the authors in this study made use of a character recognition technique based on a convolutional neural network (CNN). The dataset in this technique was subjected to augmentation. The authors used various types of augmentation techniques like on-the-fly (real-time) augmentation and the offline method (data set expansion method). Out of the two methods, the on-the-fly approach accomplished an accuracy of 99.78%, and the off-line technique accomplished 99.47% accuracy.

Joseph S., et.al. (2021) [13] in this approach, there is a proposal to use a method based on a convolutional autoencoder for recognizing handwritten MODI script. The objective of the method is to try out a deep learning technique to extract features to build an efficacious character recognition approach for isolated handwritten MODI scripts. KNN classifiers are used in the classification phase to categorize features that are extracted from the autoencoder. A comparison of the performance of two distinct classifiers like SVM and KNN is also undertaken in this method. As result, the KNN classifier had achieved 99.4% and SVM had achieved 99.3% accuracy.

Tamhankar P.A. et al. [14] have applied the algorithm by using the Rectified Linear Unit neuron activation function in the convolutional layers and the softmax neuron activation function in its fully connected layer in this method. The method uses the max pooling layer to detect features. The design of the model calls for 32 convolutional filters with a size of $3 \times 3 \times 1$. The model is trained to make use of over 40000 samples of characters that belong to 31 varying class labels. The neural network that was trained was tested using over 10000 character samples and accomplished an overall accuracy of 65%.

Mahajan K. et al. [15] have primarily use the CNN algorithm. Experimentation is being performed on a dataset of 58 handwritten characters with 100 variation images of each character and CNN with Alexnet model achieved 89.72 % accuracy.

Chandra S. et al.[8], the authors here have created an image dataset for handwritten MODI characters along with Deep CNN (DCNN) and Alexnet as a network that is pre-trained for transferring weights for retraining the network. This network employs a feature extractor used for extracting features from the various layers of the network. In order to procure classifier models; a Support Vector Machine (SVM) is trained on activation features. The authors have formulated the problem in two domains, source, and target as, $D_s = \left(X_I^S\right\}|_{i=1}^{n_s}$ and $D_t = D_t^I \cup D_t^I = (X_i^t\}|_{i=1}^{n_t^I} \cup (X_i^t\}|_{i=1}^{n_t^0}$ *and where* X_i^s , X_i^t are the inputs in source (training and testing) and target domain with size n_s and n_t, respectively. The authors obtained accuracy of 92.32% in recognizing handwritten MODI characters.

Shah R. et al.[16], in this work the authors focused on three main challenges of the MODI OCR. The first one is that there are no boundaries for any of the words resulting in all the words being connected. This leads to the length of a word being much more than words in any other Indian language. The second challenge is that the documents written in MODI are all primarily handwritten. The third challenge is that the text is written on documents that are making line segmentation harder. The goal of this network is to resolve the first concern using a deep neural network. The CNN Model focused here takes the input image and produces a features map of V' = (D*H*W). D denotes the number of output channels which is 512. H and W denote feature map height and width which are image height as well as image width divided by 8 after max-pooling respectively. The authors produced 303571 MODI line images synthetically along with noise as well as a blur for this experiment utilizing a MODI_SAHO font that was developed in-house. This experiment describes the usage of OpenNMT architecture used in recognition because of flexible hyperparameter tuning and the usage of a neural encoder-decoder model with an attention technique for the MODI OCR. The authors assessed the performance of the text recognition using the images that had been produced synthetically. The evaluation of this method was based on the text output of the line images. The authors attained 99.97% accuracy with the use of this test.

Joseph S. et al.[17], the authors of this study came up with a proposal based on the application of two techniques that use the distance classifier approach for classifying MODI script that is handwritten. The first experimental setup used the Euclidean distance classifier and the second setup used the Manhattan distance classifier. The respective accuracies obtained were 99.28% and 94%.

Joseph S.et al.[18], a discussion of the implementation of a feature extractor that employs a CNN autoencoder for the MODI script to recognize characters is undertaken in this work. For the features to be classified next, the features are fed to the Support Vector Machine classifier. In this research, RBF kernel is used, which is expressed a, $K(x,x) = expexp\left(-\frac{\|x-x\|^2}{2\sigma^2}\right)$. Where $\|x_i - x_j\|^2$ is recognized as square Euclidean distance between two vectors and s is a kernel parameter. The accuracy reported in this work is 99.3% and the size of the data is 4600 MODI Characters.

Parag Tamhankar et al.[19], in this work, the authors undertake to segment individual characters from MODI documents that are handwritten. As the characters of one line are written with the hand not being lifted, the outcome of the Vertical Projection Profile (VPP) technique is not adequate. The approach presented here is a novel one to isolate individual characters that use a criterion of dual thresholding for minimizing the error of character segmentation. The accuracy of character segmentation is 67%.

Sawant S. et. al.[20], the primary goal of this study was bridging the gap between the two scripts, Devanagari and MODI with the development of a method for mapping MODI characters that have been recognized to their corresponding characters in the Devanagari script. The dataset of the authors is made up of 57 varying classes of MODI script characters. The authors proposed a deep-learning CNN architecture with little pre-processing for character recognition. The goal of the method is to come up with a good rate of recognition.

Mahajan K. et al.[21], the authors in this research work investigate the concerns that arise during the digital transcription of ancient text documents that are handwritten and highlight the concluding remarks of analytical research.

Kulkarni S. A. et al.[22], the main interest of this study was a proposal for Partial Character Recognition (PCR) for the MODI script and a performance evaluation of the method proposed here with an application of varying classifiers. The partial area of character (PAC) represented the percentage of partialness in the image of the character. PAC was extricated with the use of different planar geometrical shapes that included a square, a circle, a rhombus, and a triangle. The application of these shapes helped discover patterns and find areas and lengths of the PAC which in turn aided in the estimation of the extent to which a given ideal character was incomplete. The framework in this study undertakes an analysis of the experimental outcome along with Decision Tree, k-NN, LDA and QDA, Naïve Byase, and SVM as compared to Euclidean distance classifiers. Research has revealed the percentage of confidence in the recognition rate (CRR) at 94.92% for making use of Zernike moments and 97.68% for the partial handwritten MODI characters making use of soft computing methods along with an integrated approach.

Solley J. et al.[18], here in this study, the authors came up with an overview of the different feature extractors as well as classifying methods that are used in recognizing the MODI characters. They also provided an assessment and a comparison of these methods.

Deshmukh M. et al.[23], this approach has come up with a multistep technique for the segmentation of the MODI script characters based on an assessment of the density of the background pixel of the global and local horizontal zones of the text line. The segmentation of the isolated, overlapping, and touching characters is achieved with efficiency by making use of the proposed MODI character segmentation approach.

Solanki B. et al.[24], the work in this research tries to enhance image eminence, improve the contrast value and also segregate the background and foreground information. There is a proposal in the study for binarizing the images of the MODI characters with efficiency. The authors used two performance parameters for measuring the effect of the varying thresholding techniques. These performance parameters are mean square error and peak signal-to-noise ratio. The outcome of this states that Otsu thresholding method demonstrates an effective way of binarizing the MODI vowels in a more appropriate form.

Deshmukh M. et al.[25], the authors have come up with an innovative technique for segmenting text lines in handwritten, unconstrained, and freestyle MODI scripts. Making use of the estimated location of the text region, estimation and segmentation of the true text line location are undertaken. The authors apply this new approach recursively on the estimated line segments till there is no separation in the individual text lines. The technique can manage different types of documents such as non-uniform Shirorekha, multi-skewed, variable-sized characters or text tones, and touching as well as overlapping line segments proving the robustness of the algorithm. Various old handwritten MODI documents are used to test and compare this technique.

Maurya R. K. et al.[26], in this research, the authors have described the framework of digital character recognition of handwritten MODI script, more so for the cursive writing style. To determine how much the features from the hybrid feature space contribute, this technique makes use of empirically decided heuristics. The hybrid feature space utilizes a normalized chain code along with a feature vector that encompasses multiple holes, endpoints as well as zones that are associated with a specific character. The results showed an average and best performance for recognition using the method proposed herein at 91.20% and 99.10% respectively. An experimental outcome demonstrates that the empirical model that is proposed is appropriate for discrete MODI script characters. The work done in this study produces a potential for a model that is independent of the size of the handwritten characters along with those characters that have loops and occluding structures. The outcome also reveals that the framework is independent of the writing style and it applies to cursive as well as non-cursive variants of the MODI script.

Shekhar, Chatterjee[20], in this thesis has worked on a description of a design for a logically modified font type for the MODI script. The premise is that this will be used in the printing of educational books, websites as well as mobile applications. The primary goal of this research work was an investigation of the requirement for new fonts needed for the Modi script. Previously no uniform standards for character encoding existed for the MODI script. Considerable efforts on the part of Mr. Anshuman Pandey resulted in the creation of this font in Unicode. The contribution of this work will be helpful to restore MODI script historical documents digitally by using these fonts and it will benefit beginners in learning the MODI script with the creation of informational books.

This research work will proceed in the direction of MODI Lipi Handwritten Character Recognition with the analysis and relevance of other languages which have nearly the same pattern of characters as that of MODI. MODI can be mainly compared with the Devanagari script since the basis of MODI is the same model as the Devanagari script. The difference is in letterforms and rendering behaviors of the characters. There are certain similarities in the shapes of some of the vowels, consonants, and vowel signs. Some environments like the consonant-vowel combinations as well as consonant conjuncts which are the basic features of the MODI script reflect the real differences in the way these characters behave.

Patil P.A.[27], in this research, the focus of the author is on the extraction of literature from the MODI script. The work is done on a detailed algorithm required for MODI script OCR. In the devised solution, after the initial stage of segmentation, this research concentrates on extracting features making use of Affine Moment Invariants (AMIs) to calculate the moments of each character. These moments are utilized in building training and testing databases. Subsequently, Fuzzy Logic classification is performed. In results, AIMs-based classification has given highly reliable results in case the deformation that occurs between the templates and the unknown characters is more or less affine. The features extracted by AMIs are more or less similar to the differences in handwriting, but some character features can give rise to complexity. The authors have defined the scope of the work to improve the success rate of their work despite major differences in characters that are a result of different styles of handwriting. Affine moment invariants (AMIs) - general affine transformation is given by, u = ao+a1x+a2y and v = bo+b1x+b2y where (x,y) and (u,v) are coordinated in the image plan before and post the transformation respectively. The four simplest AMIs utilized for character recognition are:

The mean and standard deviation are calculated for each kind of feature such as {the Mean $M_i = \frac{1}{N_i} I_i(k)$ and Std-Dev $\sigma_i = \sqrt{(I_i(k) - M_i)^2}$ Where N, represents the number of samples in the l^{th} class and I i(k) is the k^{th} feature value of reference character in the i^{th} class. In this work, for unknown input character X, the corresponding features will be extracted. The Fuzzy

Table 1. AMIs utilized for character recognition

$I_1 = 1/m^4{}_{00}(m_{20}m_{02} - m^2{}_{11})$
$I_2 = 1/m^{10}{}_{00}(m^2{}_{30}m^2{}_{03} - 6m_{30}m_{21}m_{12}m_{03} + 4m_{03}m^3{}_{21} - 3m^2{}_{21}m^2{}_{12})$
$I_3 = 1/m^7{}_{00}(m_{20}(m_{21}m_{03} - m^2{}_{12}) - m_{11}(m_{30}m_{03} - m_{21}m_{12}) + m_{02}(m_{30}m_{12} - m^2{}_{21}))$
$I_4 = 1/m^{11}{}_{00}(m^3{}_{20}m^2{}_{03} - 6m^2{}_{20}m_{11}m_{12}m_{03} + + 9m^2{}_{20}m_{02}m_{12} + 12m_{20}m^2{}_{11}m_{21}m_{03} + 6m_{20}m_{11}m_{02}m_{30}m_{03} -$ $18m_{20}m_{11}m_{02}m_{21}m_{12} - 8m^3{}_{11}m_{30}m_{03} - 6m^2{}_{20}m_{02}m_{12} + 9m_{20}m^2{}_{02}m_{21} + 12m^2{}_{11}m_{02}m_{30}m_{12} + 6m_{11}m^2{}_{02}m_{30}m_{21} + m^3{}_{02}m^2{}_{30})$

Gaussian Membership Function to get the maximum membership values,m_{xi} = exp – Where Xi represents the ith feature of the unknown character. It has preferred a database of handwritten vowels to form a trained database. It eliminates the issue of varieties in handwriting somewhat. This work is done on vowels only, which needs to enhance the success rate for variation in character because of varying styles of handwriting.

Chandure S.L. et al.[28], the creators of this system present a technique that is both, non-neural as well as neural. It can be used to classify various characters, specifically Devanagari or MODI vowels. This method uses pre-processing and extracts making use of Chain code histogram as well as Intersection junction techniques. The authors have used BN, KNN, and SVM for training and classifying characters of both, MODI as well as Devanagari. The authors compare the two scripts based on the rate of recognition. However, the rate of recognition that is acquired for MODI is less in comparison to Devanagari because vowels that have a similar shape are misclassified. Hence, a different technique is required for the MODI characters as compared to Devanagari to enhance the performance. Moreover, the rate of recognition can be raised even more by accounting for a large dataset for the process of classification.

A. Kulkarni Prashant et al.[29], this study attempted to express the effectiveness of Zernike Complex moments and Zernike moments with different zoning patterns for recognizing handwritten MODI characters offline. Each character was broken up into six zoning patterns that had 37 zones. The zoning patterns were created utilizing geometrical shapes.

The Zernike Complex polynomial is used for the 10th order with two repetitions. Zernike moments, Z_{nm} of order n with repetition m, is defined in polar coordinates (r, Θ) inside the unit circle as follows, $Z_{mn} = \frac{m+1}{\pi}\int_0^1\int_0^{2\pi} R_{nm}(r)\,e^{-jm\theta} f(r,\theta)\,rdrd\theta,\ 0 \le (m| \le n,\ n-(m$

Where, $f(r,\theta) \approx \sum_{n=0}^{M}\sum_m Z_{nm}R_{nm}(r)\,e^{jm\theta}$ and $R_{nm}(r) = \sum_{k=0}^{\left(n-\frac{(m|}{2}\right)}(-1)^k \frac{(n-k)!}{k!\left(\frac{n-2k+(m|}{2}\right]!\left(\frac{n-2k+(m|}{2}\right]} r^{n-2k}$

This research attained a rate of recognition that was 94.92% accurate by using Zernike moments and 94.78% accurate with the use of Zernike complex moments with an integrated approach for heterogeneous zones.

Kulkarni S. A. et al.[30], the issue of identifying shapes in Handwritten Optical Character Recognition (HOCR) has been addressed by the authors in this work. To enhance the results, extracting features is addressed by definition of the shape of the character in as precise and unique a manner as possible. The methodology of the Zernike moments describes shapes; identifies rotation invariant due to its characteristic of Orthogonality. This study also describes the efficacy of Zernike moments in comparison to Hu's seven moments with zoning for automatic recognition of MODI script characters that are handwritten. In Hu's Seven Moments,$\phi_1\ to\ \phi_6$are defined as absolute orthogonal invariants moments that are not dependent on position, size, and orientation and $\phi_7$is the skew orthogonal invariant. These features can recognize properties of characters and numerals. Hu's seven invariant moments are defined as:

$$\varnothing_1 = n_{20} + n_{02}$$
$$\varnothing_2 = (n_{20} - n_{02})^2 + 4n_{11}^2$$
$$\varnothing_3 = (n_{30} - 3\,n_{12})^2 + (3n_{21} - \mu_{03})^2$$
$$\varnothing_4 = (n_{30} - 3\,n_{12})^2 + (n_{21} + \mu_{03})^2$$
$$\varnothing_5 = (n_{30} - 3n_{12})(n_{30} + n_{12})\left((n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2\right] + (3n_{21} - n_{03})(n_{21} + \quad n_{03}[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2]$$
$$\varnothing_6 = (n_{20} - 3n_{02})\left((n_{30} + n_{12})^2 - (n_{21} + n_{03})^2\right] + \qquad 4n_{11}(n_{30} + n_{12})(n_{21} - n_{03})$$
$$\varnothing_7 = (3n_{21} - n_{03})(n_{30} + n_{12})\left((n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2\right] - (n_{30} - 3n_{12})(n_{21} + n_{03}[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2]$$

Also, Zernike moments are formed using a set of complex polynomials which form a completely orthogonal set on the unit disk with$(x^2 + y^2) = 1$. $Z_{mn} = \frac{m+1}{\pi}\int_x\int_y I(x,y)\,(V_{mn}(x,y)]\,dxdy$ Where m and n define the order of moment and I (x, y) the gray level of a pixel of the image I on which the moment is calculated.

Zernike moments that had an original image of size 60*60 were broken up into 5 zones where 4 zones were of an equal size of 30*30 and the last fifth zone overlapped one of size 31*31. The Zernike moment features are more reliable and their features are more accurate for the recognition of handwritten characters in the MODI script as compared to Hu's seven invariant moments. Moreover, zoning enhances the rate of recognition by up to 82.61%. The authors have further specified the scope of their work to be able to recognize handwritten characters from many more available historical documents.

Besekar D.N. et al.[31] This work focuses on identifying the issue of recognition of handwritten numerals in the MODI script that are offline. The authors have come up with a proposal for an algorithm for extracting features based on zones. The solution includes a further division of the character image (30 x 30) into 4 equal zones (15 each). A pixel conversion into polar coordinates for every zone is next. The Theta angle and Rh distance from the x-axis are measured to get pixel coordinates (Theta, Rh) for each pixel of the image and zone images. Then using Theta and Rh it computes the variance. This process is applied to all the numerals of the MODI script. The outcome reveals that when there is a maximum matching of the variance, it results in the recognition of numerals. This approach attained a recognition rate of 93.5% for the numerals of the MODI script. The authors have specified the further scope to produce more efficient results with a new zone-based feature extraction algorithm and extend the work to vowels and consonants of MODI script.

Ajmire P.E.[32] proposed handwritten Marathi character (Vowel) Recognition using the Feature extraction method of Seven Invariant moments and Clustering done using the Gaussian Distribution Function. Feature extraction using Seven Invariant moments is given by a function f(x,y), these regular moments are defined by, $M_{pq} = \iint x^p y^q f(x,y)dxdy$ .This is implemented using digital form, $M_{pq} = x^p y^q$ f(x, y) . The coordinates of the center of gravity of the image are calculated by, m_{pq} = $(x -)^p$ $(y -)^q$ and Clustering is performed using Gaussian Distribution Function: f(x | m, s^2) = e where μ is the mean and σ^2 is the variance. The system was verified on 10 images of each of the 12 handwritten Marathi vowels. During the performance, the average recognition rate of the vowels before clustering is 59%, and after the clustering is 62%. This work primarily focuses on vowels only.

A database search on Google Scholar, Research Gate, Science Direct, and other sites was used to conduct the current review study. Combining keywords like, “Distance Classifier, Feature Extraction and Classification, Handwritten Characters, MODI Lipi, Character Recognition” were used in the review technique. Title and abstract screening were used for the records' preliminary review. Additionally, non-extractable data, duplicate research, and inadequate information were grounds for excluding the Records.

Automatic handwriting recognition has been the focus of research for a long while due to its extensive usage as a means of communicating. The two phases of automatic handwriting recognition, namely, generation and recognition make up the basis of study models as well as fundamental techniques[33]. However, it is at best, inconsistent as a result of variations in cultures, fonts, or alphabets and varying styles of authors making it a motivating issue. Handwriting recognition has been researched for many decades but has yet to encompass numerous local languages including Modi Lipi. This survey covers the analysis of the research work done in relevance with the Modi Lipi handwritten Character recognition. In the literature there exist some pieces of work on Modi Lipi's stylistic text recognition. Here the author are analyzing key work done in the past 12 years (2010 - 2022) specifically for Modi Lipi.

CDAC, Pune took the initiative to create awareness among the new generation of users and helped in the preservation of the MODI script. CDAC has introduced an Android-based application to learn the MODI script and a web Browser Plug-in to read existing Marathi (Devanagari) websites in Marathi (MODI) which is being called Marathi (Devanagari) to Marathi (MODI) Web Converter. This helps the user to read existing Marathi Sites in MODI. Currently, it is a free plug-in that supports Chrome Browser on Windows, Mac, and Linux.

The Translation Services USA provides translation of MODI to and from any other world language by a MODI translation team (Real Human Translators) and also offers services for MODI interpretation, transcriptions, optimization of multilingual search engines, and voice-overs. The team has given an assurance that they can professionally localize any software or website and they can translate any website scripted in MODI.

Overall analysis of modi lipi research work, as shown in Tables 1 and 2.

Table 2. Represents techniques used to achieve the character recognition rate of MODI Lipi

Sr. No	Research and Year	Feature Extraction/ Any other technique	Classification /Clustering	Data type	Dataset	Accuracy
1	[34], Joseph (2022)	Wavelet transform - Daubechies, Haar, and Symlet wavelets	Decision tree	Characters	4600 MODI Characters: 3220 Training Samples and 1380 Testing Samples	Daubechies wavelet yielded better character recognition 91.75

Continued on next page

Table 2 continued

2	[13], Joseph (2020)	Convolutional Neural Network (CNN) (10 Layers)	Convolutional Neural Network (CNN)	Characters	Original 4600 MODI Characters: Data Augmentation Methods – Offline method (20, 40 Degree rotations, Gaussian, Salt, Pepper Noise), Dataset – 23,030(16100- Training Samples and 6930 Test Samples)	Data Augmentation Offline method: 99.47 On-the-fly method: 99.78% (Saves Storage Space)
3	[11], Joseph (2021)	the hybrid method called WT-SVD (Wavelet Transform-Singular Value Decomposition)	Euclidian Distance	Characters	Test Dataset	WT-SVD 99.56%: Need to work on segmentation of unconstrained MODI Script documents
4	[17], Joseph (2021)	CNN autoencoder (300-D vector was generated as a feature vector)	KNN classifier	Characters	Handwritten Test Dataset – 4600 Training Dataset: 3220 Test Dataset: 1380 Performed on-the-fly augmentation	KNN classifier: 99.4% SVM with RBF Kernel: 99.3%
5	[14], Tamhankar (2021)	Convolutional Neural Network (CNN)	Convolutional Neural Network (CNN)	Characters	40000-Character Samples belonging to 31 different class labels	Overall Accuracy is more than 65%.
6	[13], Mahajan (2021)	Convolutional Neural Network (CNN) with Alexnet model	Convolutional Neural Network (CNN)	58 Handwritten characters	Each character has 100 different variations of images	89.72 %
7	[8],Chand (2021)	Deep Convolutional Neural Network (DCNN) with ReLU	Support Vector Machine (SVM)	46 classes (characters)	4600 character samples were written by 100 participants	92.32%
8	[19], Chandure (2021)	Deep Convolutional Neural Network (DCNN) using AlexNet and GoogLeNet	Deep Convolutional Neural Network (DCNN)	46 classes of characters	27,600 character samples	95.86% using GoogLeNet
9	[22], Kulkarni (2021)	Zernike and Zernike Complex moments	Decision Tree, k-NN, LDA and QDA, Naïve Byaseand SVM, Euclidian distance classifier	46 handwritten characters	100 repetitions of each character	94.92% confidence in recognition rate (CRR) using Zernike moments and 97.68% for Partial MODI handwritten character using soft computing techniques

Continued on next page

Table 2 continued

10	[16], Shah	Convolutional Neural Network (CNN)	Convolutional Neural Network (CNN)	Line Level	303571 MODI line images synthetically with noise and blur, Synthetic & Augmented: Train- 121428, Test - 91072, Validation- 91071	Based on the OpenNMT architecture uses (The PARAM SHAVAK Workstation),99.97% accuracy for Modi OCR at 90000 step size
11	[35], Joseph (2020)	Vectorization (2D)	Euclidean Distance and Manhattan Distance Classifier	46 (Characters)	100 Samples of each character	Euclidean Distance – 99.28%, Manhattan Distance – 94%
12	[13], Joseph	CNN autoencoder	Support Vector Machine (SVM)	Characters	4600 MODI Characters: 3220 train samples and 1380 test samples	99.3 %
13	[36], Sawant, (2020)	Deep Convolutional Neural Network (DCNN) (Map the recognized MODI characters to their Devanagari equivalent)	Deep Convolutional Neural Network (DCNN)	57 different classes of Characters	57000 Handwritten images	2 Architectures: 1- 2 convolutional layers, max pooling, and fully connected layers 200 epochs-95.44% 2- 3 convolutional layers, max pooling, and 3 fully connected layers 200 epochs-95.97%
14	[26], Maurya (2018)	Chain Code	Empirically determined heuristics	33 Characters	60 handwritten documents with nearly 3200 characters	91.20%
15	[37], Garde (2016)	Hybrid–Combination of Invariant and Affine Moment Invariant	SVM Classifier	Characters	3 Datasets with Modi letter samples Dataset 1 - 700, Dataset 2 -700, Dataset 3 - 600	Average recognition rate 89.72% Dataset 1- 89.71%, Dataset 2 - 90.14%, Dataset 3 -89.33%
16	[28], Chandure (2016)	Chain Code Histogram & Intersection/Junction features	KNN, BPNN and SVM classifier	Vowels	Approximately 30 writers were asked to write on the given datasheet except writing characters in the boxes, no constraints were enforced	Chain code(KNN-60% BPNN-37.5% SVM-65%) and Intersection/Junction features (KNN-40% BPNN-15% SVM-47.5%)
17	[27], Patil (2016)	Affine Moment Invariants are used for calculating the moments of each character	Fuzzy Logic	Vowels	Unclear Handwritten vowels to form a trained database	Unclear Up to some extent overcomes the problem of varieties in handwriting

Continued on next page

Table 2 continued

18	[38], Kulkarni S. (2015)	The efficiency of Zernike moments over Hu's seven moments with zoning	Euclidian Distance	Characters	100 samples of each 46 basic 'MODI' characters to form a 4600 character set and the Total data set was of size 23000 images for 5 zones and 41400 images for 9 zones	82.61% (Zernike)
19	[29], Kulkarni (2015)	Zernike Complex moments and Zernike moments with different Zoning patterns	Euclidian Distance	Characters	100 samples of each 46 basic 'MODI' characters to form a 4600 character set and divided into 37 zones to form a data set of 170200 images	94.92% (Zernike) & 94.78% (Complex)
20	[31], Berserker	Chain code histogram and normalized chain code histogram	Feedforward NN	Vowels	65 handwritten pages	65.3% to 73.5%

Table 3. Represents techniques used to process MODI Lipi documents

Sr. No	Author	Technique	Data type	Dataset	Accuracy/ Outcome
1	[39], Translation-Services USA [dated: 26 Feb. 2022]	–	Not Applicable	Not Applicable	Offers services for MODI interpretation, transcriptions, etc.
2	[23], Tamhankar (2020)	(Character Segmentation with Author's proposed algorithm)	Characters	More than 15000 characters	Characters Segmentation - 67%
3	[23], Deshmukh (2019)		Text lines	3000 handwritten Modi documents (1052 text lines)	character segmentation Successful Segmentation Rate (SSR) 85.08%
4	[24], Solanki ,(2018)	A threshold model is proposed for binarizing Modi character images efficiently Otsu Global Thresholding Technique	Numerals	For binarizing 168 samples of Modi character components	Otsu thresholding technique gives more accurate results for binarizing Modi numerals
5	[25], Deshmukh, (2018)	–	Text lines	2540 document images	Text line segmentation Accuracy - Unclear
6	[40], Tamhankar ,(2018)	skew detection, skew correction using affine transformation, and shirorekha extraction by focusing consecutive foreground pixels	Complete Line	Out of 216 samples, skew detection and correction were done for 203 samples whereas, shirorekha extracted for 195 samples	Skew detection, correction- 93.98% and shirorekha extraction 90.27%

Continued on next page

Table 3 continued

7	[41], (2011)	Pandey,	Representation in plain text at the character level Encoding in a new script block to be named 'Modi'	All Modi Letters	Unicode Characters	Unicode Characters: 11600;MODI LETTER A;Lo;0;L;;;;;N;;;;; 11601;MODI LETTER AA;Lo;0;L;;;;;N;;;;; . . . . . 11650.11659; NU # DIGIT ZERO DIGIT NINE.

2 Conclusion

The Modi script has historical significance as it was used to write the Marathi language until the 1950s. Character recognition for the Modi script is still in its infancy due to the complexity of the script. Character recognition will become more accurate if more effective techniques are used at each step of the process. Each existing Modi script "character recognition system" is looked into in this paper for effective analysis. A variety of character recognition techniques have been used successfully for MODI Lipi, including OCR, neural networks, HMMs, SVMs, and CNNs. The choice of technique will depend on the specific requirements of the application and the available training data. A variety of methods with different efficiencies have been proposed to recognize MODI scripts. The authors of this study have examined several techniques used to identify the Modi script and concluded that the maximum accuracy of "Convolutional Neural Network" (CNN) is 99.78% and the yield and detection result of WT-SVD ("Wavelet Transform-Singular Value Decomposition") method is 99.56%. As per the findings of the present study the author has evaluated CNN and SVD as the best method of character recognition for Modi script which provides the maximum accuracy rate.

Acknowledgment

The authors wish thanks to all the referees involved in the above-mentioned work of MODI Lipi character recognition review and analysis.

References

1) Chandankhede C, Sachdeo R. Offline MODI script character recognition using deep learning techniques. *Multimedia Tools and Applications*. 2023;82(14):21045–21056. Available from: https://doi.org/10.1007/s11042-023-14476-0.
2) Deshmukh M, Patil M, Kohle S. The Divide-and-Conquer based algorithm to detect and correct the skew angle in the old age historical handwritten MODI lipi documents. *International Journal of Computer Science and Applications*. 2017;14(2):47–63. Available from: https://apps.nmu.ac.in/naac/0/3/all/345/427.pdf.
3) Chandure S, Vandana Inamdar. Offline Handwritten MODI Character Recognition Using GoogLeNet and AlexNet. *2021 The 13th International Conference on Computer Modeling and Simulation*. 2021. Available from: https://doi.org/10.1145/3474963.3474974.
4) Jadhav S, Vandana Inamdar. Convolutional Neural Network and Histogram of Oriented Gradient Based Invariant Handwritten MODI Character Recognition. *Pattern Recognition and Image Analysis*. 2022;32(2):402–418. Available from: https://doi.org/10.1134/S1054661822020109.
5) Joseph S, Datta A, Anto O, Philip S, George J. OCR System Framework for MODI Scripts using Data Augmentation and Convolutional Neural Network. *Data Science and Security*. 2021;p. 201–209. Available from: https://doi.org/10.1007/978-981-15-5309-7_21.
6) Pawar V, Wadkar D, Kashid S, Prakare P, More V, Babar A. MODI Lipi Handwritten character Recognition using CNN and Data Augmentation Techniques. *International Research Journal of Engineering and Technology*. 2022;p. 1880–1884. Available from: https://www.irjet.net/archives/V9/i6/IRJET-V9I6337.pdf.
7) Das S, Wankhede K, Rituraj A. Review on Modi Handwritten Characters Recognition. *International Research Journal of Modernization in Engineering Technology and Science*. 2022;(11):1267–1274. Available from: https://www.irjmets.com/uploadedfiles/paper/issue_11_november_2022/31334/final/fin_irjmets1668970066.pdf.
8) Chandure S, Vandana Inamdar. Handwritten MODI Character Recognition Using Transfer Learning with Discriminant Feature Analysis. *IETE Journal of Research*. 2021;p. 1–11. Available from: https://doi.org/10.1080/03772063.2021.1902867.
9) Kulkarni SA, Borde PL, Manza RR, Yannawar PL. Offline Handwritten MODI Character Recognition Using HU, Zernike Moments and Zoning. 2014. Available from: https://doi.org/10.48550/arXiv.1406.6140.
10) Sachdeva R. Comparative Analysis Zoning , Distance Profile Feature And K- Nearest Neighbour For Handwritten Devanagari Script Recognition System. 2021. Available from: https://www.webology.org/abstract.php?id=3695.
11) Joseph S, George J. Efficient Handwritten Character Recognition of MODI Script Using Wavelet Transform and SVD. *Data Science and Security*. 2021;p. 227–233. Available from: https://doi.org/10.1007/978-981-15-5309-7_24.
12) Joseph S, George J. Data Augmentation for Handwritten Character Recognition of MODI Script Using Deep Learning Method. *Information and Communication Technology for Intelligent Systems*. 2021;p. 515–522. Available from: https://doi.org/10.1007/978-981-15-7062-9_51.

13) Joseph S, George J. Handwritten Character Recognition of MODI Script using Convolutional Neural Network Based Feature Extraction Method and Support Vector Machine Classifier. *2020 IEEE 5th International Conference on Signal and Image Processing (ICSIP)*. 2020;2020. Available from: https://doi.org/10.1109/ICSIP49896.2020.9339435.
14) Tamhankar PA, Masalkar KD, Kolhe SR. Character Recognition of Offline Handwritten Marathi Documents Written in MODI Script Using Deep Learning Convolutional Neural Network Model. *Communications in Computer and Information Science*. 2021;p. 478–487. Available from: https://doi.org/10.1007/978-981-16-0507-9_40.
15) Mahajan KN, Tajne N. An Ancient Indian Handwritten Script Character Recognition by Using Deep Learning Algorithm. 2021. Available from: https://www.researchgate.net/publication/355096343_An_Ancient_Indian_Handwritten_Script_Character_Recognition_by_Using_Deep_Learning_Algorithm.
16) Shah R, Gupta MK, Kumar A. Line Level Modi (Heritage script) OCR using Attention based Encoder-Decoder Architecture. *2021 Sixth International Conference on Image Information Processing (ICIIP)*. 2021;p. 273–278. Available from: https://doi.org/10.1109/ICIIP53038.2021.9702605.
17) Joseph S, George J. Convolutional Autoencoder Based Feature Extraction and KNN Classifier for Handwritten MODI Script Character Recognition. *Data Science and Security*. 2021;290:142–149. Available from: https://doi.org/10.1007/978-981-16-4486-3_15.
18) Joseph S, George J. Feature extraction and classification techniques of modi script character recognition. *Pertanika Journal of Science and Technology*. 2019;27(4):1649–1669. Available from: http://www.pertanika2.upm.edu.my/resources/files/Pertanika%20PAPERS/JST%20Vol.%2027%20(4)%20Oct.%202019/12%20JST-1336-2018.pdf.
19) Tamhankar PA, Masalkar KD, Kolhe SR. A Novel Approach for Character Segmentation of Offline Handwritten Marathi Documents written in MODI Script. *Procedia Computer Science*. 2020;171:179–187. Available from: https://doi.org/10.1016/j.procs.2020.04.019.
20) Shekhar C. Designing a New Digital Font for Modi - Script. *Ergonomics International Journal*. 2018;2(4). Available from: https://medwinpublishers.com/EOIJ/EOIJ16000150.pdf.
21) Nilesh K, Pundlikrao N. Transliteration of Indian Ancient Script to Braille Script using Pattern Recognition Technique: A Review. *International Journal of Computer Applications*. 2017;166(6):33–38. Available from: https://doi.org/10.5120/ijca2017914162.
22) Kulkarni SA, Yannawar PL. Recognition of Partial Handwritten MODI Characters Using Zoning. *Communications in Computer and Information Science*. 2021;p. 407–430. Available from: https://doi.org/10.1007/978-981-16-0507-9_35.
23) Deshmukh MS, Kolhe SR. A Hybrid Character Segmentation Approach for Cursive Unconstrained Handwritten Historical Modi Script Documents. *SSRN Electronic Journal*. 2019. Available from: http://dx.doi.org/10.2139/ssrn.3356213.
24) Solanki B, Ingle M. Performance Evaluation of Thresholding Techniques on Modi Script. *2018 International Conference on Advanced Computation and Telecommunication (ICACAT)*. 2018;p. 1–6. Available from: https://doi.org/10.1109/ICACAT.2018.8933594.
25) Deshmukh MS, Patil MP, Kolhe SR. A hybrid text line segmentation approach for the ancient handwritten unconstrained freestyle Modi script documents. *The Imaging Science Journal*. 2018;66(7):433–442. Available from: https://doi.org/10.1080/13682199.2018.1499226.
26) Maurya RK, Maurya SR. Recognition of a Medieval Indic-Modi Script using Empirically Determined Heuristics in Hybrid Feature Space. *International Journal of Computer Sciences and Engineering*. 2018;6(2):136–142. Available from: https://www.ijcseonline.org/pub_paper/19-IJCSE-02860.pdf.
27) Patil PA. Character Recognition System for Modi Script. *International Journal of Computational Engineering Research*. 2016. Available from: http://www.ijceronline.com/papers/Vol6_issue9/F0609031038.pdf.
28) Chandure SL, Vandana Inamdar. Performance analysis of handwritten Devnagari and MODI Character Recognition system. *2016 International Conference on Computing, Analytics and Security Trends (CAST)*. 2016;p. 513–516. Available from: https://doi.org/10.1109/CAST.2016.7915022.
29) Sadanand AK, Prashant LB, Ramesh RM, Pravin LY. Offline MODI Character Recognition Using Complex Moments. *Procedia Computer Science*. 2015;58:516–523. Available from: https://doi.org/10.1016/j.procs.2015.08.067.
30) Kulkarni S, Borde P, Manza R, Yannawar P. Recognition of Handwritten MODI Numerals using Hu and Zernike features. *CoRR*. 2014;1:1–7. Available from: https://arxiv.org/vc/arxiv/papers/1404/1404.1151v1.pdf.
31) Besekar DN. Special Approach for Recognition of Handwritten MODI Script's Vowels. *Proceedings published by International Journal of Computer Applications® (IJCA)*. 2012;p. 48–52. Available from: https://research.ijcaonline.org/medha/number1/medha1023.pdf.
32) Ajmire PE, Warkhede SE. Handwritten Marathi character (vowel) recognition . 2010. Available from: https://bioinfopublication.org/files/articles/2_2_3_AIM.pdf.
33) Chandankhe C. Handwritten MODI Lipi Barakhadi Dataset. *IEEE Dataport*. 2023. Available from: https://doi.org/10.21227/x24n-wm25.
34) Joseph S, George JP. Offline Character Recognition of Handwritten MODI Script Using Wavelet Transform and Decision Tree Classifier. *Information and Communication Technology for Competitive Strategies (ICTCS 2020)*. 2022;p. 509–517. Available from: https://doi.org/10.1007/978-981-16-0739-4_48.
35) Joseph S, George JP, Gaikwad S. Character Recognition of MODI Script Using Distance Classifier Algorithms. *ICT Analysis and Applications*. 2020;p. 105–113. Available from: https://doi.org/10.1007/978-981-15-0630-7_11.
36) Sawant S, Sharma A, Suvarna G, Tanna T, Kulkarni S. Word Transcription of MODI Script to Devanagari Using Deep Neural Network. *2020 3rd International Conference on Communication System, Computing and IT Applications (CSCITA)*. 2020. Available from: https://doi.org/10.1109/CSCITA47329.2020.9137781.
37) Gharde SS, Ramteke RJ. Recognition of characters in Indian MODI script. *2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC)*. 2016;p. 236–240. Available from: https://doi.org/10.1109/ICGTSPICC.2016.7955304.
38) Sadanand AK, Prashant LB, Ramesh RM, Pravin LY. Impact of zoning on Zernike moments for handwritten MODI character recognition. *2015 International Conference on Computer, Communication and Control (IC4)*. 2015;4. Available from: https://doi.org/10.1109/IC4.2015.7375516.
39) Translation Services USATM - Accurate Translation of Documents. . Available from: https://www.translation-services-usa.com/.
40) Tamhankar PA, Kolhe SR. kew Detection, Skew Correction , and Shirorekha Extraction Of Line Segmented Offline Handwritten Historical Marathi Documents Written In MODI. 2018. Available from: http://dx.doi.org/10.21172/1.101.62.
41) Pandey A. Final Proposal to Encode the MODI Script in ISO / IEC 10646. 2011. Available from: https://www.unicode.org/L2/L2011/11212r2-n4034-MODI.pdf.